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Potential Distribution Projections for *Senegalia senegal* (L.) Britton under Climate Change Scenarios

Jiaqi Fang [1,2], Jianfei Shi [1,2], Ping Zhang [1,2], Minghao Shao [1,2], Na Zhou [1,*], Yongdong Wang [1] and Xinwen Xu [1]

1 Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, China; ajin187514@163.com (J.F.); shaominghao20@mails.ucas.ac.cn (M.S.); wangyd@ms.xjb.ac.cn (Y.W.)
2 University of Chinese Academy of Sciences, Beijing 100049, China
* Correspondence: zndesert@ms.xjb.ac.cn

Abstract: The gum acacia *Senegalia senegal* (L.) Britton (Fabales: Fabaceae) is a drought-tolerant plant belonging to the genus *Acacia* of the Leguminosae family, possessing significant economic and ecological value. Despite its importance, there is a knowledge gap regarding the potential impact of climate change on the distribution of *S. senegal*, crucial for the conservation of plant resources and optimizing its use in introductory silviculture. In this study, we selected 23 environmental variables and utilized the optimized maximum entropy (MaxEnt) model to analyze the key environmental factors affecting the distribution of *S. senegal* worldwide and simulate the current and future distribution range of *S. senegal* in Pakistan under the SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 climate change scenarios. The results highlight key environmental factors influencing the distribution of *S. senegal*, including BIO3 (isothermally), BIO4 (coefficient of seasonal variation of temperature), BIO11 (mean temperature of the coldest season), and BIO12 (annual precipitation). Regions with higher and less fluctuating temperatures exhibit a higher potential for *S. senegal* distribution. Currently, suitable habitats of *S. senegal* are concentrated in the southern region of Pakistan, covering provinces such as Punjab, Sindh, and Balochistan, with highly suitable habitats accounting for 6.06% of the total area. Under the current climatic conditions, this study identifies the spatial patterns of suitable habitats and their concentration in specific regions. With climate change, a notable expansion of suitable habitats towards higher latitudes is observed, with the most significant expansion under the extremely severe climate change scenario (SSP5-8.5), reaching 223.45% of the current level. The results of this study enhance our understanding of the dynamics of *S. senegal* distribution under climate change and offer valuable insights into the long-term introduction of *S. senegal* for afforestation and soil conservation in Pakistan. This study provides theoretical support for the sustainable development of the local ecosystem and socio-economy, emphasizing the importance of proactive measures to adapt to changing climatic conditions.

Keywords: MaxEnt model; climate change; species distribution; *Senegalia senegal* (L.) Britton; Pakistan

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1. Introduction

Approximately 1/4th of the world's land area is affected by desertification, and the establishment of protective forests is an important preventive and control measure adopted by countries to address ecological problems and natural disasters, particularly desertification [1–3]. The gum acacia *Senegalia senegal* (L.) Britton (Fabales: Fabaceae), which grows predominantly in tropical and subtropical arid zones, is an important multipurpose agroforestry species in desert regions [4,5]. It boasts widespread economic applications with a low-input production cycle and the gum Arabic it yields can be used in foods, beverages, feed, pharmaceuticals, cosmetics, industrial products, and fuelwood [6,7]. *Senegalia senegal* has demonstrated ecological value in addition to its economic versatility, and *S. senegal*-based agroforestry systems have been used for centuries in the Sahel, adapting to climate, topography, and geomorphological and anthropogenic changes [8]. Additionally, *S. senegal* exhibits the capability to fix atmospheric nitrogen (N_2), increasing the soil inorganic nitrogen content and microbial biomass, presenting a potential alternative to address the scarcity of chemical fertilizers in the arid regions of Africa and counteract declining fertility resulting from shortened fallow periods [9–11]. Therefore, *S. senegal* plays a vital role in advancing socioeconomic development, maintaining agro-ecosystem stability, and facilitating ecological restoration and construction in arid areas, making it an optimal choice for protective forest species.

Species distribution models (SDMs) quantify a species' ecological niche and project it onto a spatially referenced model. SDMs have become advantageous tools for predicting the potential geographical distribution and habitat suitability of species and are widely used across various disciplines [12–14]. Among SDMs, the maximum entropy model (MaxEnt), a machine learning method, determines the ecological requirements of species based on their distribution records and environmental factors [15,16]. Due to its broad applicability, objectivity, and high reliability, MaxEnt is extensively utilized in predicting species habitat areas, including the Chinese fir *Cunninghamia lanceolata* (Lamb.) Hook (Pinales: Cupressaceae) [12], the spiny-bellied frog *Quasipaa boulengeleri* (Günther, 1889) (Anura: Dicroglossidae) [14], the long tube lousewort *Pedicularis longiflora* (Rudolph) (Lamiales: Orobanchaceae) [17], and others. Although MaxEnt modeling has been widely studied, there are fewer projections of species distributions under the four carbon emission climate scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Most studies utilize global climate models (GCMs) from individual institutes, which do not accurately and comprehensively represent changes in habitat areas under future climate change scenarios [18–20]. Therefore, studying the habitat change of *S. senegal* under different climatic conditions is essential to enhance the success of plantation introduction.

The arid and semi-arid land area of Pakistan, constituting 80% of the national territory, has undergone severe degradation and desertification [21]. The introduction of *S. senegal* for afforestation is effective in alleviating desertification. However, limited knowledge exists regarding the distribution of potentially suitable habitats for *S. senegal*, particularly in the context of significant global climate change. Climate change exerts profound impacts on the geographic distribution and population dynamics of species, potentially hastening the loss of biodiversity [22–25]. For instance, Alabar et al. [26] forecasted the distribution of eight tropical dry forest plant species and observed a southward shift in their potential range. Guo Yanlong et al. [27] discovered that, under the most extreme warming scenarios, 22 tree species in southern China may lose over 50% of their potential distribution area. Tiago et al. [28] predicted that, due to climate change, the endemic orchid species *Prosthechea jauana* (Carnevali & I. Ramírez) W.E.Higgins (Orchidales: Orchidaceae) in Venezuela could lose up to 92% of its habitat by 2080. Therefore, investigating the environmental variables and suitable habitats of *S. senegal* amidst climate change and understanding the influence of environmental factors on its distribution can offer scientific and theoretical support for planning *S. senegal* planting areas.

In this study, we utilized the MaxEnt model and ArcGIS 10.8, incorporating current (1970–2000) climatic data and *S. senegal* distribution point data, to comprehensively analyze globally suitable habitats for *S. senegal* and identify the key environmental factors influencing its distribution. Additionally, we projected the potential distribution pattern of *S. senegal* in Pakistan in the future using climate data for four SSP scenarios, each representing different greenhouse gas emission intensities, across four future periods (2020–2040, 2040–2060, 2060–2080, and 2080–2100). In this study, we aim to elucidate the key environmental factors influencing the distribution of *S. senegal* worldwide, as well as the spatial pattern changes of *S. senegal* distribution in Pakistan under the backdrop of global climate change. Our goal is to provide a reference for the conservation and rational utilization of *S. senegal* plant resources and contribute insights for long-term afforestation planning programs.

2. Material and Methods

2.1. Occurrence Data

The occurrence data for *S. senegal* were collected from the Global Biodiversity Information Facility (GBIF; http://www.gbif.org), the Chinese Virtual Herbarium database (CVH; http://www.cvh.ac.cn), and the National Specimen Information Infrastructure (NSII; http://www.nsii.org.cn/2017/home.php). A total of 2711 occurrence data points were collected. Direct use of sample information with accurate latitude and longitude was made, while the coordinate information of sample points with place names but lacking coordinate information was completed via Google Earth. To prevent sampling bias from resulting in overly dense local distribution points and overfitting the model, it was imperative to meticulously screen and proofread the obtained coordinate point data using the R package "ENMeval v2.0.0" to remove overfitting data. It was ensured that the spatial resolution of the recorded occurrence matched that of the environmental variables. Ultimately, 1117 records of the global distribution of gum acacia trees were collected (Figure 1). As shown in Figure 1, *S. senegal* is mainly distributed in Africa, with some distribution in India in Asia. Its occurrence is predominantly in regions with tropical desert and tropical grassland climates, being greatly influenced by temperature and precipitation.

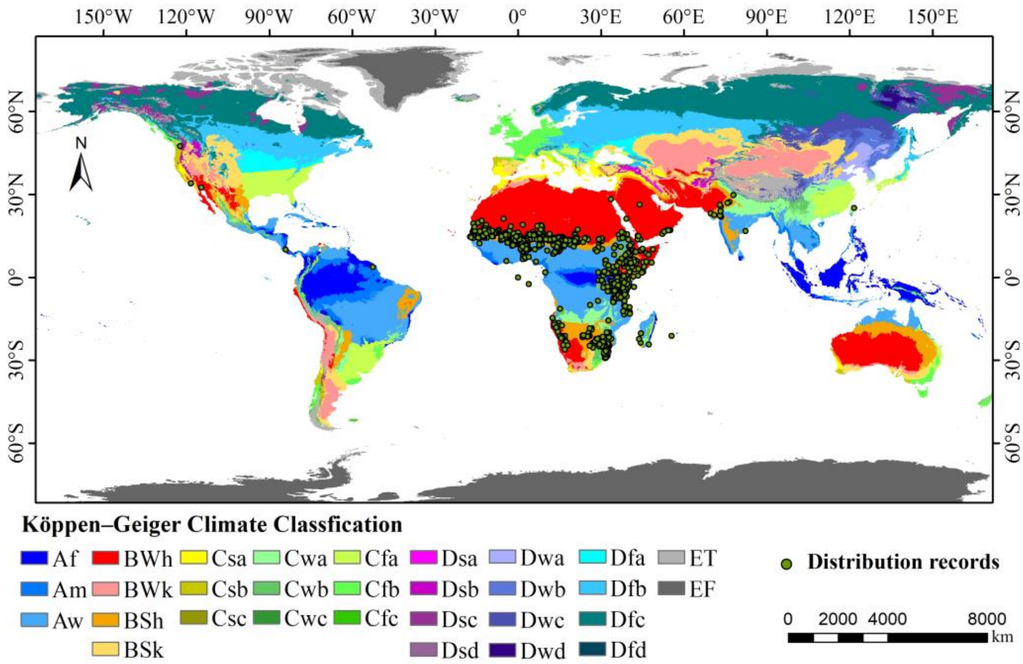

Figure 1. Global distribution status of *S. senegal*. (Abbreviations in the map follow those of the Köppen–Geiger climate classification map [29]).

2.2. Environment Variables

We selected 23 environmental variables to model under the current (1970–2000) and future (2020–2100) climate prediction scenarios, encompassing 19 bioclimatic variables (BIO1–BIO19), elevation (Elev), soil available water content (AWC), topsoil salinity (TS), and subsoil salinity (SS) (Table 1). The Harmonized World Soil Database (HWSD; http://www.fao.org/soils-portal/) provided AWC, TS, and SS, while the WorldClim2.1 database (http://www.worldclim.org/) provided the 19 bioclimatic variables and elevation data at a spatial resolution of 2.5 Arc-min. For all future scenarios, all four types of shared social economy pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) were selected as environmental data sources. Moreover, to mitigate climate uncertainty arising from a single climate model, the average of future climate simulation data from four different institutes (MIROC 6, BCC-CSM2-MR, CNRM-CM 6-1, and CanESM5) was employed for future climate data [30].

Table 1. Potential environmental factors affecting *S. senegal* distribution.

Number	Variable	Percent Contribution	Permutation Importance
1	Isothermality (BIO3)	30.5	8.1
2	Precipitation of driest month (BIO14)	12.7	0.3
3	Mean temperature of coldest quarter (BIO11)	10	33
4	Precipitation of coldest quarter (BIO19)	5.9	1.4
5	Annual mean temperature (BIO1)	5.5	0
6	Annual precipitation (BIO12)	5.3	22.4
7	Precipitation seasonality (BIO15)	4.6	3.3
8	Precipitation of wettest month (BIO13)	3.7	0
9	Available Water Content (AWC)	3.6	5.7
10	Min temperature of coldest month (BIO6)	3.2	10.5
11	Max temperature of warmest month (BIO5)	2.6	0
12	Mean temperature of warmest quarter (BIO10)	2.3	0.6
13	Mean temperature of wettest quarter (BIO8)	2	0.1
14	Mean diurnal range (BIO2)	1.9	0.1
15	Precipitation of wettest quarter (BIO16)	1.3	2.6
16	Temperature seasonality (BIO4)	1.1	6
17	Precipitation of warmest quarter (BIO18)	0.9	1.9
18	Mean temperature of driest quarter (BIO9)	0.7	0
19	Elevation (Elev)	0.6	1.1
20	Temperature annual range (BIO7)	0.5	1
21	Topsoil salinity (TS)	0.5	1.2
22	Precipitation of driest quarter (BIO17)	0.2	0.7
23	Subsoil salinity (SS)	0.2	0

Correlations between environmental variables, all of which are used for model prediction, can lead to overfitting. Therefore, environmental variables were first analyzed for correlation using the R package "ENMTools v1.0.4" to obtain correlation coefficients (Figure 2). Then, based on the observed contributions of all environmental factors during the model training process (Table 1), environmental factors with correlation coefficients $|r| \geq 0.8$ and contribution rates < 1.0 were excluded from the modeling process to reduce the risk of overfitting caused by collinearity. Following that, seven environmental variables demonstrating statistical and biological significance were selected from the 23 environmental factors for inclusion in the modeling process: BIO3, BIO11, BIO12, BIO14, BIO15, BIO19, and AWC.

2.3. Modeling Optimization

When simulating species distribution, MaxEnt is typically executed using default parameters. However, this may result in overfitting and increased complexity, reducing result accuracy. Hence, enhanced parameter optimization is imperative [31]. In this study, the R package "ENMeval" was used to optimize the MaxEnt model [32]. Eight regularization multipliers (RM) ranging from 0.5 to 4 at intervals of 0.5 were systemically combined with six feature combinations (FC): L, LQ, H, LQH, LQHP, and LQHPT. The Akaike information criterion correction (AICc) was used to evaluate the degree of fit and complexity of the model. Typically, the combination with a delta.AICc = 0 is considered the optimal choice [33,34]. In this study, when RM = 2 and FC = LQHPT, delta.AICc = 0, indicating this optimal parameter combination was used for MaxEnt modeling.

2.4. MaxEnt Modeling and Evaluation

Occurrence records of *S. senegal* and seven environmental variables were imported into MaxEnt 3.4.4. The optimal parameter combination (RM parameter set is 2, FC parameter set is LQHPT) was adopted. The maximum number of iterations was set to 10,000. The data output format was configured as logistic. Using cross-validation to extract the test set, all occurrence records are randomly divided into 10 equally sized subsets for iteration. For each iteration, one subset is selected as the validation set, and the remaining 9 subsets are used as the training set. The MaxEnt model is trained on the training set and validated on the corresponding validation set to obtain the model performance metrics. This process is repeated ten times to obtain the average values, thus mitigating uncertainty.

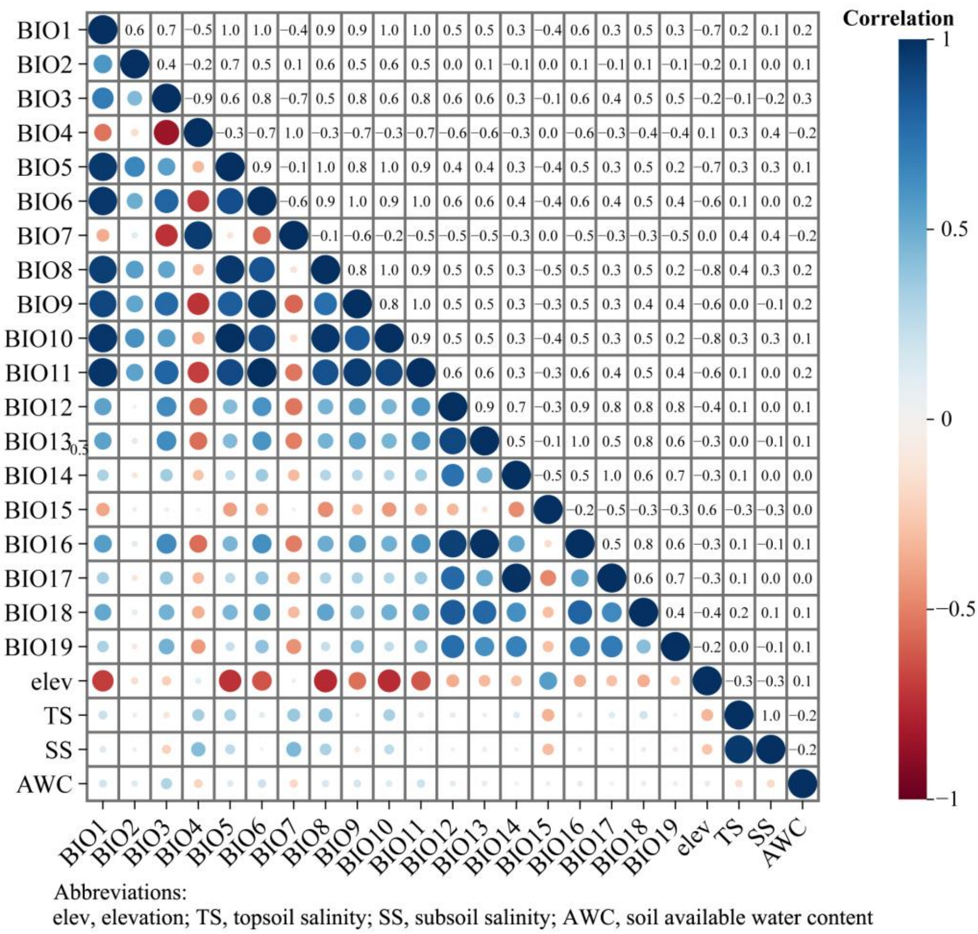

Figure 2. Climate factor correlation heat map.

The accuracy assessment primarily relied on evaluating the area under the receiver operating characteristic (ROC) curve of the MaxEnt model output. The area under the curve (AUC) ranged from 0 to 1, with higher values indicating increased confidence in predictions. An AUC value <0.8 suggested low confidence, 0.8–0.9 indicated good accuracy and 0.9–1.0 represented excellent accuracy [35]. In this study, the AUC values of the 10-fold cross-validation range from 0.926 to 0.943, with a standard deviation of 0.005 and a mean of 0.933, signifying excellent accuracy.

2.5. Classification of Suitable Regions and Spatial Pattern Changes

The suitability values for *S. senegal*, as predicted by the MaxEnt model, were continuous raster data ranging from 0 to 1, with higher values indicating greater suitability for species growth. In the current classification of suitable areas, the Jenks natural break classification method was used to categorize habitats into four groups: inappropriate, low-suitability, medium-suitability, and highly suitable. This grouping strategy, utilized in future distribution models, ensures consistent grouping with minimized errors, thereby reducing the uncertainty associated with climate change [36].

Utilizing the current habitat as the standard, SDMtolbox in ArcGIS10.8 was used to classify habitat changes into three categories: unchanged, expanding, and shrinking. This classification was based on disparities between habitats under varying climatic conditions and their counterparts in the present environment. Changes in the geometric center position of habitats with medium and high suitability under different climatic conditions were calculated. Comparative analyses were conducted on the overall trends in the core suitable area of *S. senegal* across different periods to elucidate the influence of environmental changes on its distribution over time.

3. Results

3.1. Assessment of Key Environment Variables

Based on the output of the MaxEnt model, along with regularization training gain, test gain, contribution rate, and displacement importance from the knife-cutting method, this study identifies key environmental variables affecting the geographical distribution of *S. senegal* (Figure 3, Table 1). Table 1 shows that BIO3, BIO14, and BIO11 were the three environmental variables with the highest contribution rates, totaling 53.26%. BIO11, BIO12, and BIO6 were the top three factors with the highest permutation importance, accounting for 65.89%. As shown in Figure 3, the highest regularization training gains during univariate simulation were observed for BIO4 (1.1449), BIO3 (1.1403), and BIO6 (1.1102), whereas the three variables with the highest test gains were BIO4 (1.1736), AWC (1.1696), and BIO3 (1.1577). This suggests that these variables contain crucial information. Notably, when simulating nonspecific variables, the most significant reductions in regularization training gain, test gain, and AUC values were evident for BIO12 and AWC, indicating that these variables contain information that is not present in other variables. In summary, the dominant environmental variables influencing the distribution of *S. senegal* are BIO3 (isothermality), BIO4 (temperature seasonality), BIO11 (mean temperature of coldest quarter), and BIO12 (annual precipitation).

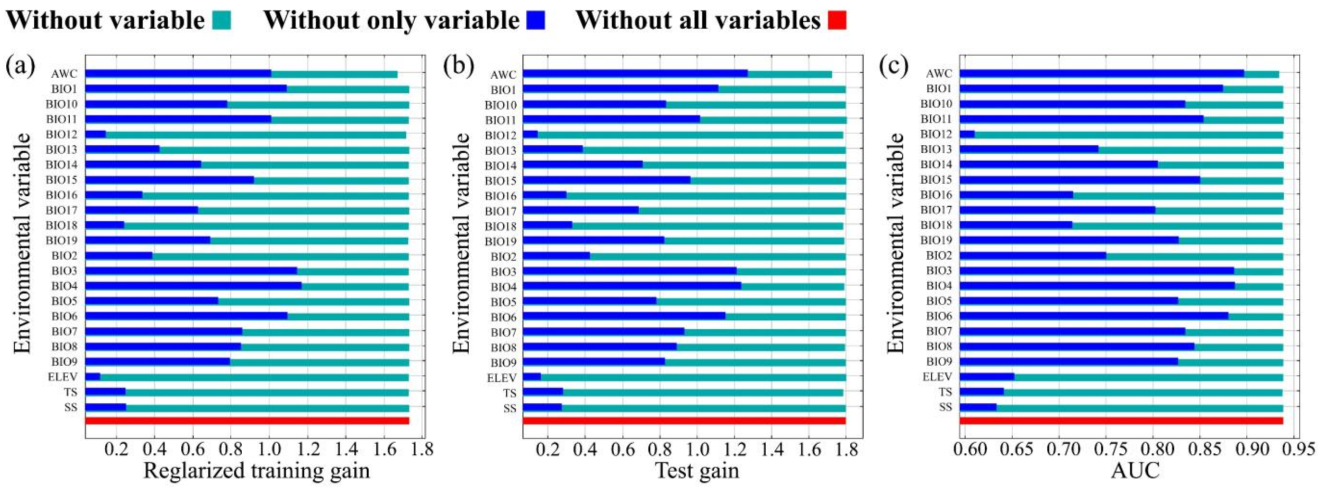

Figure 3. Evaluation of environmental factors using the jackknife method (**a**–**c**).

3.2. Response Curve Analysis of Key Environmental Variables

The single-factor response curve, derived from logistic regression analysis of key environmental factors, elucidates the relationship between the occurrence probability of *S. senegal* and environmental variables, offering insights into the impact of each dominant environmental variable on suitable habitats. Instances where the probability of occurrence exceeded 0.5 were considered conducive to plant growth. The probability of *S. senegal* occurrence was minimal when BIO3 was below 40, gradually increasing and peaking at BIO3 = 56.01, then decreasing with further BIO3 increments. BIO3 favored the growth of *S. senegal* within the range of 52.5–71.8. (Figure 4a). The BIO4, BIO11, and BIO12 trends were similar to those of BIO3, which showed an increasing-to-decreasing pattern. Optimal peaks for BIO4, BIO11, and BIO12 were 291.1, 25.19 °C, and 1014.7 mm, respectively. Occurrence probabilities above 0.5 were observed when BIO4 ranged from 115.9–416.31, BIO11 from 18.2–35.8 °C, and BIO12 from 129.88–1263.6 mm, favoring *S. senegal* growth (Figure 4).

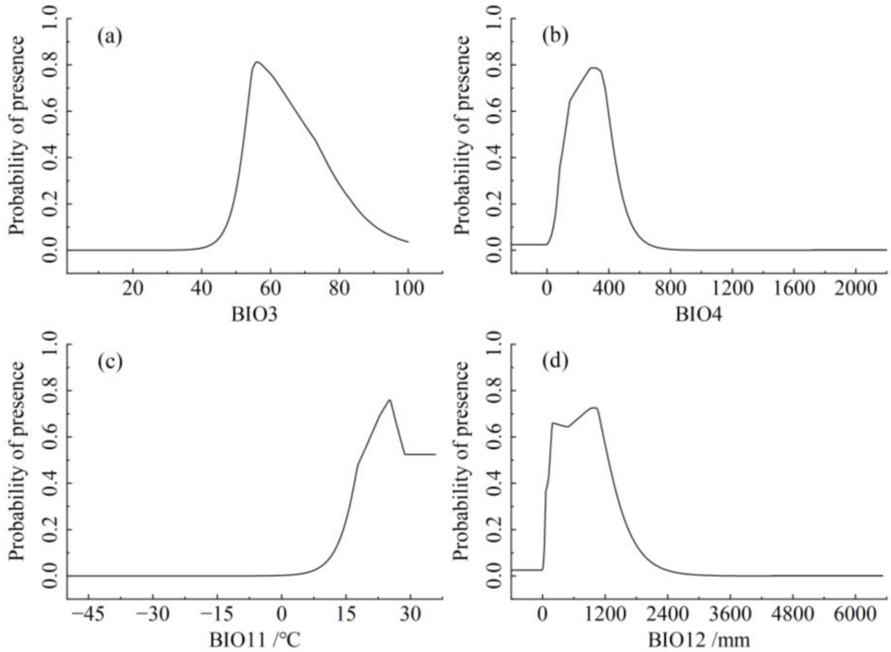

Figure 4. The relationship between potentially suitable areas and single factor response variables. (**a**) BIO3 (Isothermality); (**b**) BIO4 (Temperature seasonality); (**c**) BIO11 (Mean temperature of coldest quarter); (**d**) BIO12 (Annual precipitation).

3.3. Potentially Suitable Habitats under Current Climatic Conditions

The suitable distribution of *S. senegal* worldwide is shown in Figure 5. Among 1117 occurrence records of *S. senegal*, only 1.62% were found in unsuitable habitats. The model simulation of potentially suitable habitats broadly aligns with the occurrence records. These suitable habitats are predominantly concentrated in the tropics and subtropics, encompassing an area of 3.63 × 107 km^2. Africa exhibits the broadest distribution, harboring the largest range of highly suitable habitats. Additionally, potentially suitable habitats are identified in South America, Oceania, and Southern Asia, demonstrating areas of notable suitability.

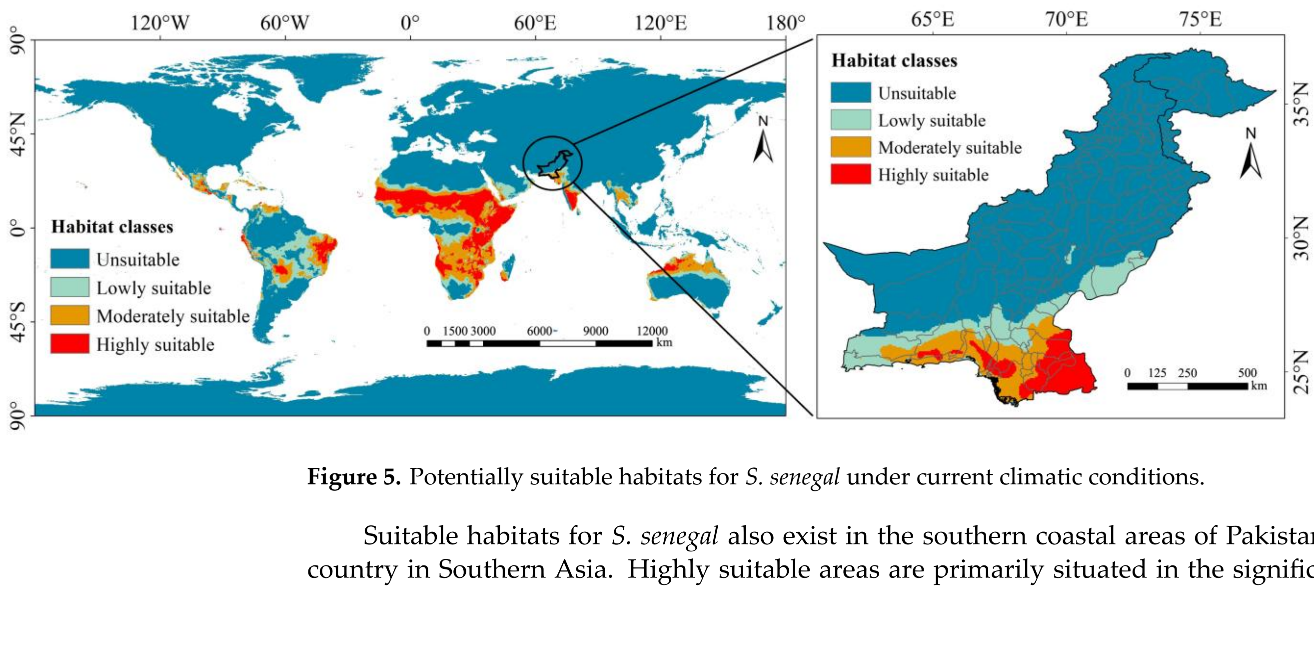

Figure 5. Potentially suitable habitats for *S. senegal* under current climatic conditions.

Suitable habitats for *S. senegal* also exist in the southern coastal areas of Pakistan, a country in Southern Asia. Highly suitable areas are primarily situated in the significant cities of Karachi and Tharparkar in the Sind Provinces, covering an area of 53,300 km^2, accounting for 6.06% of Pakistan's total area. Medium-suitable areas include the eastern regions of the Gwadar District in Balochistan Province, as well as the southern regions of Sindh Province, covering an area of 70,300 km^2, which accounts for 7.99% of the total area of Pakistan. Areas of low suitability cover 97,000 km^2 or 11.02% of Pakistan's total area, mainly located in the Sind Province, Bahawalpur and Rahimyar Khan Districts of Punjab Province, and Makran Division, Awaran, and Khuzdar Districts of the Balochistan Province.

3.4. Potentially Suitable Habitats in Pakistan under Different Future Climate Scenarios

The habitats suitable for *S. senegal* under various climatic scenarios for the next four periods (2020s–2040s, 2040s–2060s, 2060s–2080s, and 2080s–2100s) are shown in Figure 6. Medium and highly suitable habitats continue to concentrate in the southern coastal areas of Pakistan, demonstrating an overall expanding trend, whereas low-suitable habitats experience significant expansion from the southern coasts northward into the Islamabad Capital Territory.

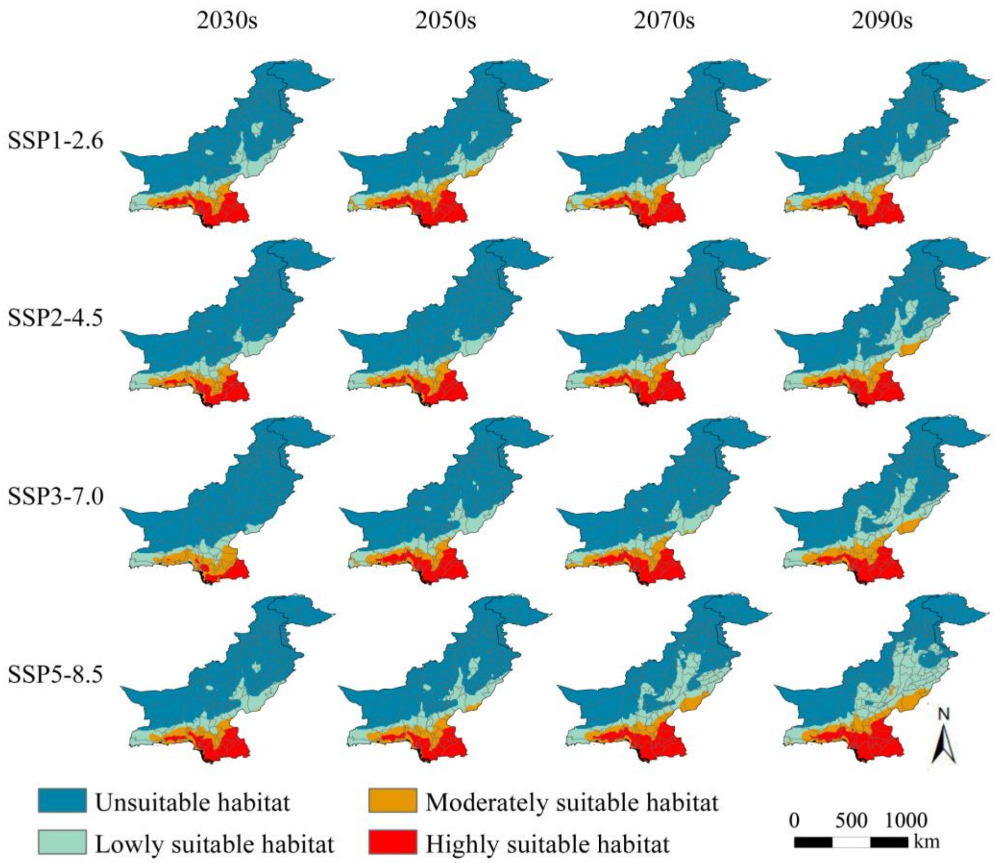

Figure 6. Potentially suitable habitat for *S. senegal* under future (2020–2100s) climatic scenarios. (The figure uses the 2030s to represent the 2020–2040s, 2050s to represent the 2040–2060s, 2070s for the 2060–2080s, and the 2090s to represent the 2080–2100s. Similarly, thereafter).

In the SSP1-2.6 scenario, the total suitable habitat for *S. senegal* experiences limited variability, ranging from 112.97%–125.37% of the current suitable distribution area, indicating an overall expanding trend. A reduction in total suitable area is observed only in the 2070s compared to the preceding period (2050s). However, all subsequent four periods of medium-suitability habitats show a decrease compared to the current one, with a maximum reduction of 21.75%.

In the SSP2-4.5 scenario, the total suitable habitat gradually expands over time to 105.77% of its current size by the 2030s and 140.79% by the 2090s. The middle-suitable habitat demonstrates relative stability, exhibiting a trend of initial contraction followed by expansion, with an expected reach of 102.00% by the 2090s.

In the SSP3-7.0 scenario, the total suitable habitat contracts to 86.16% of its current size in the 2030s and then gradually increases, with a significant expansion observed in 2090, reaching 151.56% of its current size. The medium-suitability habitat showed an expansion–contraction–expansion trend. The highly suitable habitat experiences a notable contraction in the 2030s to 63.94% of the current level, followed by gradual expansion.

In SSP5-8.5, a substantial increase in the total suitable habitat was observed, expanding to 118.55% of the current size in the 2030s, 130.16% in the 2050s, 161.58% in the 2070s, and nearly doubling to 195.60% of the current size by the 2090s. No significant changes were observed in the medium-suitable areas. The most significant change occurs in the highly suitable habitat, expanding to 223.45% of its current size by the 2090s.

3.5. Spatial Pattern Changes of Potential Habitat Regions in Pakistan

With increasing climatic severity (SSP1-2.6 to SSP5-8.5) and the passage of time, the medium and high habitats of *S. senegal* continued to expand slowly northward, reaching as far as the Bahawalpur District in Punjab Province. The shrinkage of suitable areas is infrequent and mainly occurs in the central part of the Gwadar District in Balochistan Province. The stable area, encompassing the eastern Gwadar District, southern Karat District, and most regions of Sindh Province, remained the largest in proportion and exhibited minimal change (112,200 km^2 to 127,400 km^2) (Figure 7).

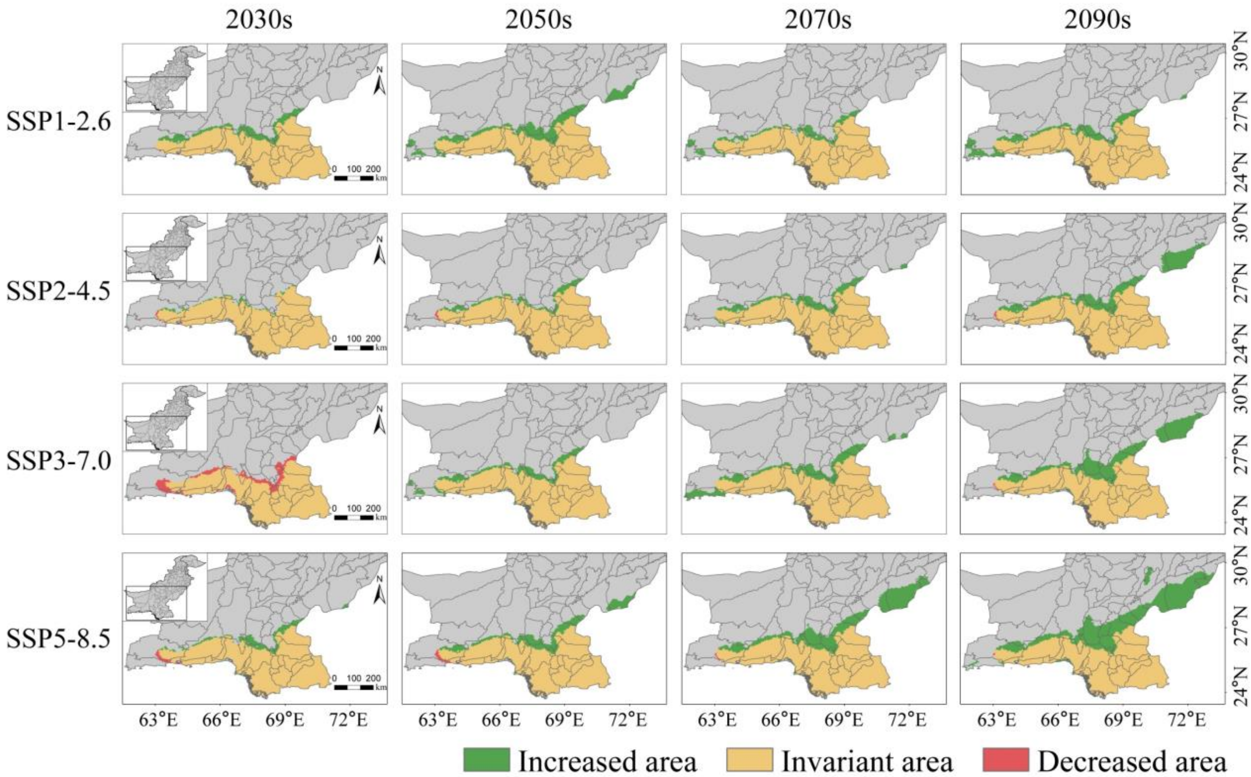

Figure 7. Changes in potentially suitable areas of *S. senegal* from current to future climatic conditions.

The geometric center point of the potentially suitable distribution area (distribution center) of *S. senegal* tended to migrate northward in different scenarios and at different times (Figure 8). In the SSP2-4.5 scenario, the distribution center migrated 56.27 km to the northeast in the 2050s, 82.79 km to the northeast in the 2070s, and 52.61 km to the northwest in the 2090s. In the SSP5-8.5 scenario, the migration of the distribution center is the most significant, especially in the 2050s, with a migration of 208.17 km to the northeast compared with the current. In the current climate scenario, the distribution center is situated in the Khuzdar District. By the 2090s, in each climate scenario, the distribution center has migrated to the Dadu and Qambar Districts near the Indus River basin. At different time periods, the magnitudes of four key environmental factors at the distribution center also change (Table 2). Compared to the present, in the 2090s, BIO3 and BIO12 both exhibit a significant decrease, while BIO4 and BIO11 show a significant increase.

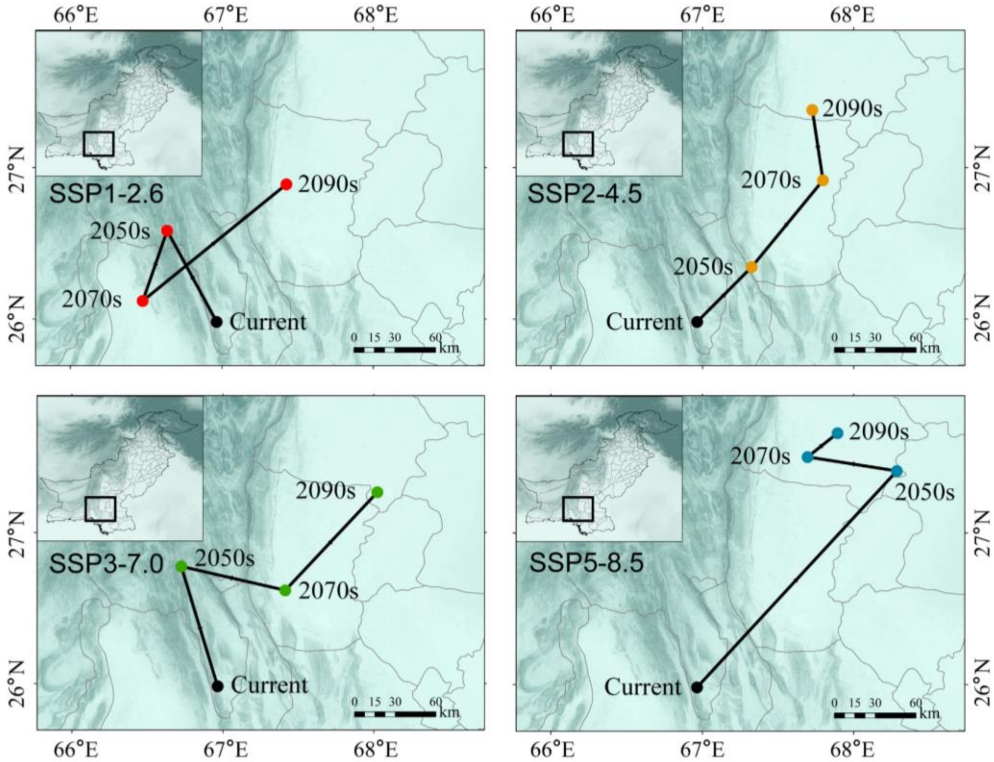

Figure 8. Distribution center shift of *S. senegal* from current to future climatic conditions.

Table 2. Changes in key environmental factors at the distribution center under future climate conditions.

Environmental Variables	Climate Scenario	Current	2050s	2070s	2090s
BIO3	SSP1-2.6	48.65	45.14	50.44	44.51
	SSP2-4.5	48.65	43.19	42.65	39.62
	SSP3-7.0	48.65	43.48	43.59	39.29
	SSP5-8.5	48.65	41.43	38.48	37.08
BIO4	SSP1-2.6	550.62	626.35	563.49	744.97
	SSP2-4.5	550.62	653.49	744.72	768.59
	SSP3-7.0	550.62	642.31	704.32	737.19
	SSP5-8.5	550.62	743.82	753.74	756.59
BIO11/°C	SSP1-2.6	16.81	15.46	21.31	19.30
	SSP2-4.5	16.81	17.98	19.79	20.07
	SSP3-7.0	16.81	15.52	21.24	21.33
	SSP5-8.5	16.81	19.55	21.60	22.83
BIO12/mm	SSP1-2.6	424.00	507.50	245.25	145.25
	SSP2-4.5	424.00	285.75	145.25	129.00
	SSP3-7.0	424.00	454.75	165.25	129.00
	SSP5-8.5	424.00	121.75	132.75	122.25

4. Discussion

4.1. Effects of Environmental Variables on the Distribution of S. senegal

The geographical distribution of plants is mainly affected by climate [37], with hydrothermal conditions playing a dominant role in the distribution pattern of plants [38].

The knife-cut method, employed to derive training gain, contribution, and single-factor response curves, elucidates crucial environmental factors affecting species distribution. Waheed et al. [39] identified BIO1, BIO3, BIO8, and BIO12 as key bioclimatic variables influencing the growth of the Bengal quince *Aegle marmelos* (L.) Corrêa (Sapindales: Rutaceae) in Pakistan. Similarly, Khan et al. [40] demonstrated the significance of BIO3, BIO11, and BIO14 in determining the occurrence of the chilghoza pine *Pinus gerardiana* Wall. ex D. Don (Pinales: Pinaceae) in South Asia (Afghanistan, Pakistan, and India). Bhandari et al. [41] highlighted BIO4, BIO7, BIO12, and BIO15 as major climatic factors influencing the distribution of the tree rhododendron *Rhododendron arboreum* Sm. (Ericales: Ericaceae) in the central Himalayas. In this study, the most significant environmental factors affecting *S. senegal* distribution were identified as BIO3, BIO4, BIO11, and BIO12. Temperature factors (BIO3, BIO4, and BIO11) determine species adaptations and affect plant germination, growth, and development [42]. For example, BIO3, indicative of temperature change magnitude, is related to plant temperature sensitivity and cumulative temperature effectiveness [43]. Moisture factors (BIO12) play a key role in plant growth and water balance, directly influencing growth stability [42,44,45].

The use of environmental response curves facilitates the understanding of the relationship between species distribution probability and climatic variables. This study reveals that the distribution potential of *S. senegal* is higher in areas with higher and less fluctuating temperatures within a given range (Figure 4a–c). Precipitation also influences the distribution potential of *S. senegal*, with a higher probability of occurrence in areas with lower annual rainfall and a lower probability of occurrence in areas with higher annual rainfall (Figure 4d). Previous studies, including the work by Raddad et al. [46], have shown that the natural distribution area of *S. senegal* is primarily on stabilized sand dunes with an annual rainfall of approximately 280 mm or on sandy soils within the 280–500 mm isopach lines. Diatta et al. [4] reported that *S. senegal* usually grows in arid areas with low soil fertility and rainfall ranging from 200–800 mm. The results from this study further demonstrate that a suitable habitat for *S. senegal* is minimally affected by soil physicochemical properties, exhibits low soil fertility requirements, and has a high growth potential with rainfall between 129.88 and 1263.6 mm. In summary, our research findings regarding the suitable habitat range for *S. senegal* are similar to but not entirely consistent with other studies, which may be attributed to the multifaceted nature of plant survival influenced by various environmental factors [47–49]. While the response curve of a single factor can reflect the overall trend of its impact on plant survival, deriving thresholds from it as the suitable range for plants with regard to that factor is inaccurate. Additionally, we considered bioclimatic variables, topography, and soil factors in assessing the distribution of *S. senegal*. However, environmental factors influencing plant distribution may extend beyond these, and future research could incorporate additional environmental variables for modeling to achieve more accurate estimates of species potential distribution.

4.2. Changes in Suitable Habitat for S. senegal in Pakistan

Utilizing the MaxEnt model with optimized parameters, this study identified suitable distribution areas for *S. senegal* in the Sindh, Balochistan, and Punjab Provinces of Pakistan under current climatic conditions. Climate change can significantly impact the range of species, prompting migration to higher latitudes or altitudes [50,51]. Future projections, as indicated by increased precipitation intensity in the Northern Hemisphere's middle and high latitudes, alongside higher temperatures and increased CO_2 concentrations [52], suggest a potential adaptation of species to these changing conditions. The results of this study show that the range of *S. senegal* in Pakistan under the present climatic conditions was between 24° N and 30° N (Figure 6). However, under the four future climate change scenarios, the range of *S. senegal* will continue to expand to higher latitudes, potentially reaching a maximum range of 24–34° N (Figure 7). Similar to our study findings, Ashraf et al. [53] found that in Pakistan, the habitat of the Indian olive tree *Olea ferruginea* (syn. *Olea europaea* subsp. cuspidata) (Wall. & G.Don) Cif. (Lamiales: Oleaceae) in high-altitude and high-latitude areas will increase under future climate change scenarios. Ali et al. [54] showed that the west Himalayan fir *Abies pindrow* (Royle ex D.Don) Royle (Pinales: Pinaceae) in Pakistan migrate to higher latitudes owing to global warming and climate change. The economically important crop *P. gerardiana* Wall. in South Asia also shows a trend of northward migration [40]. In addition, species in various regions around the world are also following their suitable climatic conditions. For example, in Africa, the endemic rose *Rosa arabica* (Crép. ex Boiss.) Déségl. (Rosales: Rosaceae) in Egypt and the African bamboo *Oxytenanthera abyssinica* (A.Rich.) Munro (Poales: Poaceae) in Ethiopia are both migrating to higher altitude and higher latitude areas under two future climate change scenarios [55,56]. In Europe, the ecological niche of the false acacia *Robinia pseudoacacia* L. (Fabales: Fabaceae) tends to shift northeastward with climate change [57]. In the United States of America, the potential distribution areas of three major invasive plant species will also expand northward in the future [58]. These research findings indicate that, against the backdrop of global warming, plants in various regions of the Northern Hemisphere are showing a trend of migrating towards higher latitudes and altitudes. However, the adaptive capacity of different species to extreme climate change differs, leading to significant differences in their habitat ranges under distinct climate change scenarios [39,59]. Qazi et al. [60] showed that compared to SSP2-4.5, the areas of suitable zones of the shrub *Buxus papillosa* C.K.Schneid. (Euphorbiales: Buxaceae) and the Indian gentian *Gentiana kurroo* Royle (Gentianales: Gentianaceae) decreased in Pakistan under the SSP5-8.5 scenario (2070s), whereas the area of suitable zones of the shrub *Rydingia limbata* (Benth.) Scheen & V.A.Albert (Lamiales: Lamiaceae) increased. Gilani et al. [61] showed that compared to RCP4.5, the areas of the habitable zones of the Himalayan pine *Pinus wallichiana* A. B. Jacks (Pinales: Pinaceae) and the holm oak *Quercus ilex* L. (Fagales: Fagaceae) decreased in the RCP8.5 scenario (2050s), while *A. pindrow*, and other Himalayan trees, the birch *Betula utilis* D.Don (Fagales: Betulaceae), the cedar *Cedrus deodara* (Roxb.) G.Don (Pinales: Pinaceae), and the spruce *Picea smithiana* (Wall.) Boiss. (Pinales: Pinaceae) showed an increase in the areas of their suitable habitats. In this study, compared with SSP1-2.6, SSP2-4.5, and SSP4-7.0, the area of the *S. senegal* suitable zone increased significantly under the SSP5-8.5 scenario (the 2090s), with the most significant increase in the area of the low-suitability zone, suggesting that *S. senegal* continues to have a high level of resilience, even under extreme climate change conditions.

In addition, the results of the distribution center shift in the suitable area revealed that *S. senegal* is gradually shifting to higher latitudes in Pakistan, driven by different climatic factors (Figure 8). Specifically, the migration path of the distribution centers of suitable areas for *S. senegal* generally migrated towards smaller BIO3 and BIO12 and larger BIO4 and BIO11(Table 2), and the reason for this result may be related to the physiological characteristics of *S. senegal*. Gaafar et al. [62] demonstrated that *S. senegal* can utilize a well-developed root system to improve drought tolerance in a composite agroforestry system. Githae et al. [63] showed that *S. senegal* has a strong nitrogen fixation capacity that can enhance its adaptability to arid and infertile soil environments. *S. senegal* exhibits a rare adaptive response to water and drought stress, ensuring that it produces high biomass in extremely dry environments [62,64]. In summary, *S. senegal* can respond well to drastic climate change in the future, and the extension of cultivation through *S. senegal* may help Pakistan alleviate the environmental stresses caused by extreme climate change to some extent.

4.3. Recommendations for the Introduction of S. senegal for Afforestation in Pakistan

Senegalia senegal holds economic and ecological value and demonstrates robust growth under hot, dry, and infertile soil conditions. It is well-suited for extensive cultivation in Pakistan, especially in the southern coastal areas. Pakistan faces severe challenges related to land degradation and desertification, particularly in the irrigated areas of Punjab, Sindh, and Balochistan [65]. Poor irrigation and drainage, coupled with low local rainfall and higher evapotranspiration than annual precipitation, lead to salt accumulation in the soil profile, contributing to low soil fertility, reduced crop yields, and the loss of biodiversity [66]. In addition, sandy areas are predominantly located in regions with low development potential and moving sand dunes pose a significant threat to local agricultural facilities and settlements [65,67]. The results of this study indicate that *S. senegal* is less affected by soil fertility, is suitable for survival in high-temperature and low-rainfall environments, and has a high potential for survival in Sind Province, Balochistan Province, and Punjab (Figure 5). Moreover, suitable habitats rarely shrink under different climate change scenarios, tending to expand even under extreme climate change conditions (Figure 7). Therefore, we propose implementing *S. senegal* afforestation in the three southern provinces of Pakistan (Sindh, Balochistan, and Punjab), especially around the Cholistan, Thal Doab, Thar, and Kharan Desert patches, which will be crucial for protecting the security of agricultural production and promoting socioeconomic development.

5. Conclusions

In this study, the optimized MaxEnt model was used to predict potentially suitable habitats for *S. senegal* under four climate change scenarios ranging from positive to extremely severe. This predictive modeling offers a theoretical foundation for the judicious utilization and sustainable scientific management of *S. senegal* plant resources. Under current climatic conditions, suitable habitats are predominantly concentrated in the southern region of Pakistan, spanning the provinces of Punjab, Sindh, and Balochistan. Hydrothermal conditions, represented by BIO3, BIO4, BIO11, and BIO12, emerge as pivotal factors influencing the suitability of habitats for *S. senegal*. Notably, under various future climate change scenarios, habitats conducive to *S. senegal* rarely shrink, with an overarching tendency to expand towards higher latitudes, particularly under extremely severe climate change scenarios. Therefore, it is recommended to implement afforestation initiatives for *S. senegal* in the southern coastal areas of Pakistan, particularly in Gwadar, Lasbela, Karachi, Thatta, and Tharparkar. This strategic approach aims to enhance the success rate of *S. senegal* introductions and provide a reference for Pakistan's afforestation efforts for sand stabilization, land protection, and ecological sustainability.

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